

Automatic event picking in pre-stack migrated gathers using a probabilistic neural network

Gregory A. Clark and Michael E. Glinsky
*University of California, Lawrence Livermore National Laboratory
Livermore, CA, L-399, P.O. Box 808, Livermore, CA 94550*

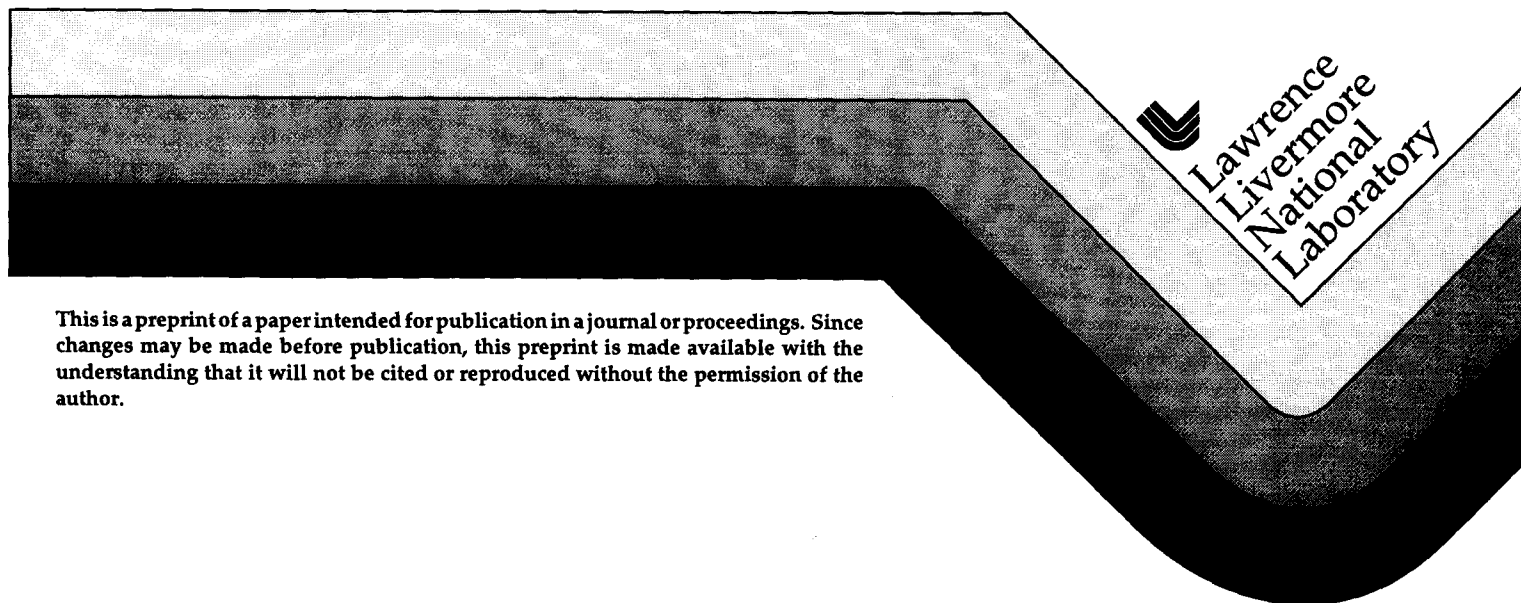
K. R. Sandhya Devi and James H. Robinson
Shell E&P Technology Company

Peter K. Z. Cheng and Gary E. Ford
University of California, Davis

This paper was prepared for submittal to:

The Proceedings of the
1996 Society of Exploration Geophysicists
November 10-15, 1996, Denver, Colorado

April, 1996



This is a preprint of a paper intended for publication in a journal or proceedings. Since changes may be made before publication, this preprint is made available with the understanding that it will not be cited or reproduced without the permission of the author.

Disclaimer

This document was prepared as an account of work sponsored by an agency of the United States Government. Neither the United States Government nor the University of California nor any of their employees, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial products, process, or service by trade name, trademark, manufacturer, or otherwise, does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States Government or the University of California. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States Government or the University of California, and shall not be used for advertising or product endorsement purposes.

Automatic event picking in pre-stack migrated gathers using a probabilistic neural network

Gregory A. Clark* and Michael E. Glinsky, Lawrence Livermore National Laboratory;

K. R. Sandhya Devi and James H. Robinson, Shell E&P Technology Company;

Peter K. Z. Cheng and Gary E. Ford, University of California, Davis

Summary

We describe algorithms for automating the process of picking seismic events in pre-stack migrated gathers. The approach uses supervised learning and statistical classification algorithms along with advanced signal/image processing algorithms. We train a probabilistic neural network (PNN) for pixel classification using event times and offsets (ground truth information) picked manually by expert interpreters. The key to success is in using effective features that capture the important behavior of the measured signals. We use a variety of features calculated in a local neighborhood about the pixel under analysis. Feature selection algorithms are used to ensure that we use only the features that maximize class separability. The novelty of the work lies in (a) the use of pre-stack migrated gathers rather than stacked data, (b) the use of two-dimensional statistical and wavelet features, and (c) the use of a PNN for classification.

Introduction

One of the major keys to seismic oil exploration is the estimation of the acoustic wave velocities in the various layers of the earth. It is required for depth migration in regions such as salt boundaries, which contain rapid lateral velocity variations. Velocity updating algorithms currently require lengthy labor-intensive manual event picking and tracking operations on migrated common reflection point (CRP) panels. Our research in automatic event picking is motivated by a desire to reduce event picking costs.

Our automatic event picking technique uses advanced algorithms from the areas of automatic target recognition (ATR), computer vision, and signal/image processing. Whenever possible, prior knowledge of the geophysics is incorporated into the processing algorithms to ensure physical relevance and enhance the ability to obtain meaningful results. We use supervised learning methodology to train a probabilistic neural network⁴ for pixel classification using manually-picked event times. The key to success is in using effective features that capture the important behavior of the measured signals. We use a variety of two-dimensional features calculated in a neighborhood about the pixel under analysis (see the section on feature extraction below).

Supervised learning

The event picking system is a supervised learning classifier for which we define two classes; "event" and "background" (not event). The supervised learning approach consists of two steps; classifier training based on ground truth from known samples, followed by a testing procedure based upon the trained classifier.

In the *training step*, we present the classifier with a "training set" of example event and background pixels (time-offset locations in CRP panels), along with their associated "ground truth," or prior knowledge of the true class to which each example belongs (manual classification as event or background). Once the classifier is trained using the "hold-one-out" method^{5,6} to successfully classify the training data with acceptable performance measured by probability of detection and probability of false alarm,^{5,6} we move to the *testing step*.

The *testing step* consists of using the trained classifier to process an image that was not included in the training set and making the appropriate classifications. Testing can occur in two very different ways: testing with a "testing set", and testing with an entire image. Testing with a "testing set" means that we set aside examples of event and background pixels, not using them for training, and apply the trained classifier to them. Testing with an entire image (image labeling) means that pixels of an image never processed before are classified as event (1) or background (0). A new binary labeled image is constructed by assigning to each pixel the binary values of the classifications. We also create posterior probability images (see the section on image labeling). In this study we relied on the performance measured by the hold-one-out training method and only tested on an entire image.

The event picking process consists of four main parts: preprocessing, pixel classification and labeling, region formation, and postprocessing. Pixel classification and labeling consists of feature extraction, feature selection, and image labeling. This paper focuses only the pixel classification and labeling step. Subsequent publications will describe region formation and postprocessing.⁵

Feature analysis

We adopt the view of the CRP panel as an image. This paper analyses real seismic data that yields a CRP image with 1600 time pixels and 45 offset pixels. The temporal sampling period is 4 ms, and the offset sampling period is 400 feet.

Training Set Nomination: We create a set of training pixels by the following process. First an expert picks several event times for every offset and subpoint combination in the dataset. 20 equally spaced CRP panels are chosen out of the 468 CRP panels in the full dataset. Several of the expert event picks are chosen at random from each of the 20 panels. Care is taken to ensure that the chosen training events are independent by demanding a minimum separation in time and offset between the pixels. Second, several background pixels are manually picked by an expert in each of the 20 panels. Care is taken that these picks represent a variety of background types and are independent.

Feature extraction: We use a variety of features calculated for each pixel in the training set. These features are normalized by subtracting from each feature value the mean of the feature values calculated over the ensemble of training tiles, and dividing this result by the ensemble standard deviation. This normalization makes the classifier less sensitive to absolute units, which can vary somewhat from feature to feature.

The features calculated include the following: (a) Amplitude histogram features⁷ or first order statistical moments of the estimated probability density function in an $M \times N$ neighborhood centered about the image pixel (we use $M=N=10$). We started with mean, standard deviation, skewness and kurtosis. After feature selection (described in the next section), we chose to use only the mean and standard deviation. (b) An offset coherence feature called semblance¹ calculated over the local neighborhood provides a useful indication of the coherence of the seismic traces in the offset direction. (c) Gabor transform features⁸ are derived from hierarchical multi-resolution 2D Gabor wavelet transforms of the CRP panels. These provide magnitude and phase information about the events at a variety of resolutions (scales), orientations (rotational angles) and frequencies. A variety of elliptical Gabor kernels were designed to have several different scales (with corresponding frequencies) and a variety of orientations characteristic of the CRP panel image. In figure 1, we display the magnitude of two of these Gabor transforms of

the image overlaid on the raw seismic traces. Note that the event is highlighted by the one Gabor kernel and the multiple by the other. Figure 2 displays the histograms of the absolute value of the Gabor phase over the training set for background and events. Notice that the events are picked at a well defined phase, that is, at a negative peak.

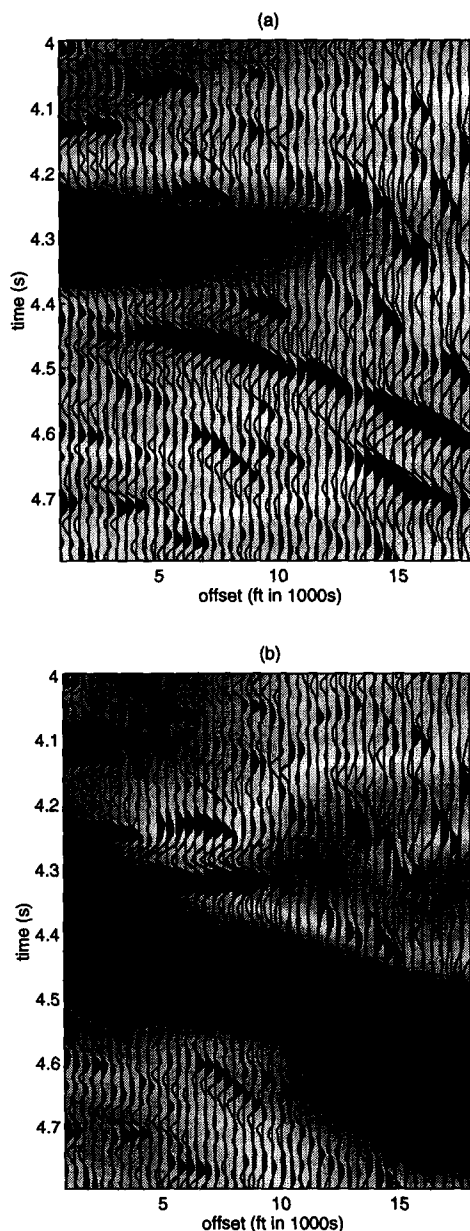


Figure 1: Magnitude of Gabor transform shown as gray scale image behind seismic data. Wavelet transform parameters are: frequency of 15 Hz, temporal width of 27 ms, offset width of 3400 ft, and (a) no slope (b) slope of 12 ms/1000 ft. Expert event picks shown as circles at 4.3 s.

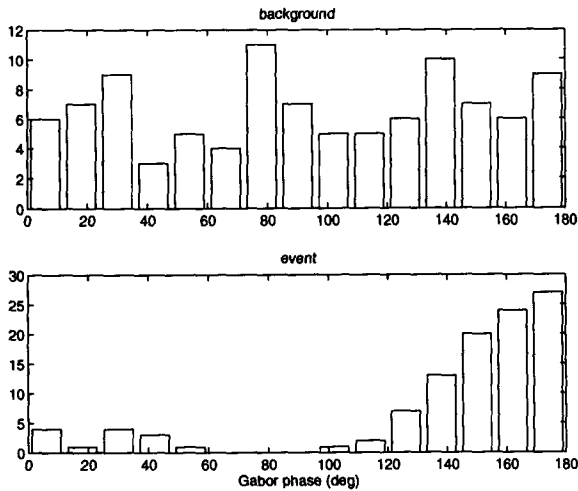


Figure 2: Histograms of absolute value of Gabor phase for same kernel used to form figure 1a. Histogram is taken over training set.

Feature Selection: We use a formal feature selection algorithm to rank order the features according to both the Bhattacharyya and Mahalanobis measures of class separability.⁶ We then choose an appropriate subset of features for actual use by the classifier. This saves computation and allows us to use only the most effective features.^{5,6} We use the well-known rule-of-thumb^{5,6} for the lower bound on the number of training samples to use – the number of independent training samples needed per class should be at least five times the number of features used in the feature vector. Note that this rule also implies an upper bound on the number of features that can be used, given the number of independent training samples. For our problem, we trained the PNN classifier with 107 event tiles and 100 background tiles. This limits us to using about 20 features, and in the analysis presented, we actually used 19 features.

Image labeling

Once the PNN classifier is trained, it is used to analyze an image not included in the training set. Two types of labeled image are created: (a) **Binary labeled image:** The PNN classifies the center pixel as belonging to either the class “event” or the class “background.” The resulting image (containing only ones representing event pixels and zeros representing background pixels) is called the “binary labeled image”. (b) **Posterior probability image:** Alternatively, the PNN computes the posterior probability

$P(\text{Event}|X)$, where X is the feature vector for the pixel under consideration. These labeled images provide us with an indication of the locations of probable event pixels. This paper does not show an example of the posterior probability image.

Processing results

During training with 100 or so samples of each class, the parameters of the PNN were tuned to achieve the best probability of correct classification. The probability of detection achieved was 89% and the probability of false alarm was 2%. This results in a probability of correct classification of 94% with a 95% confidence interval having lower bound 89% and upper bound 96%. Because of the large penalty to be paid for false alarms in subsequent seismic processing and the small penalty to be paid for missing an event, it was decided to use PNN parameters that lowered the probability of correct classification to 88% but lead to a <0.1% false alarm rate. Figure 3 shows the binary labeled CRP image and the associated seismic data. The two expertly picked events at 3 s and 4.3 s are clearly labeled as events. A more precise location of the event and a rejection of false alarms can be achieved by postprocessing the labeled images.⁵ This step is not described in this paper.

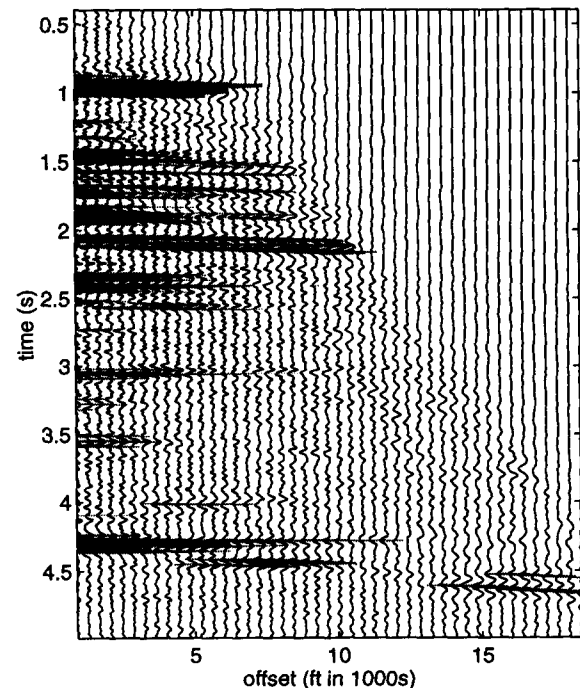


Figure 3: The binary labeled image (gray=event, white=background) plotted behind seismic data.

Discussion

Several limitations and suggestions for overcoming them are evident from this work. (1) In using a supervised learning approach, we make a leap of faith that the training set has high quality and is representative of the data to be processed. One key limitation is that our ground truth comes exclusively from the judgments of human experts, so the quality of results is only as good as the human picks. Future work includes using larger training sets. (2) Background picks are difficult to make because there are many types of background for a two-class problem (small events, multiple reflections, etc.). It could be advantageous to use multiple classes and expand the variety of background types used. (3) False alarms can exist in the labeled images, but they can be greatly mitigated by a variety of techniques which will be used in our future work. These include additional pre-processing, using of more advanced features, region formation, postprocessing and tracking of events from panel-to-panel.

Conclusions

Early work shows promise for supervised pixel classification in pre-stack migrated gathers. During training with approximately 100 samples of each class, the probability of detection achieved was 89% and the probability of false alarm was 2%. This results in a probability of correct classification of 93% with a 95% confidence interval having lower bound 89% and upper bound 96%. The events indicated in the labeled images correspond well with the ground truth picks and with large events easily discernible by eye. Some false alarm regions can exist in the labeled image. However, they consist mostly of small events that are not of interest to manual analysts, and we believe that they can be mitigated using the techniques proposed for future work.

Acknowledgments

The authors gratefully acknowledge the technical contributions of Sailes K. Sengupta of LLNL, and Cheung Tam and Ronya Yang of U. C. Davis. We especially thank our sponsors: U.S. Department of Energy through the Advanced Computing Technology Initiative (ACTI) and Shell E&P Technology Company. We thank Trilochan Padhi of Shell Oil for his important comments and suggestions.

Some of the work was performed under the auspices of the U.S. Department of Energy by the Lawrence Livermore National Laboratory under contract number W-7405-ENG-48. One of the authors (MEG) would like to acknowledge the support of a Department of Energy Distinguished Postdoctoral Fellowship.

References

1. E. A. Robinson and S. Treitel, Geophysical Signal Analysis, Prentice Hall, 1980.
2. F. Kemp, J. R. Threet, and J. Veezhinathan, "A Neural Net Branch and Bound Seismic Horizon Tracker," Extended Abstracts, 62nd Society of Exploration Geophysicists (SEG) Annual Meeting, New Orleans, 1992, pp. 10-13.
3. X. Liu, P. Xue, and Y. Li, "Method for Tracing Seismic Events," Extended Abstracts, 59th Society of Exploration Geophysicists (SEG) Annual Meeting, Dallas, Texas, 1989, pp. 716-718.
4. D.E. Specht, "Probabilistic Neural Networks," Neural Networks, Vol. 3, pp.109-118, 1990.
5. G. A. Clark, S. K. Sengupta, et. al., "Multispectral Image Fusion for Detecting Land Mines," University of California report No. UCRL-JC-120319 Invited paper, SPIE's 1995 International Symposium on Aerospace/Defense Sensing and Dual-Use Photonics, Detection Technologies for Mines and Minelike Targets, Orlando, Florida, April 17-21, 1995.
6. P. A. Devijver, and J. Kittler, Pattern Recognition: A Statistical Approach, Prentice Hall, Englewood Cliffs, 1982, p. 448.
7. A. K. Jain, Fundamentals of Digital Image Processing, Prentice Hall, 1989.
8. John G. Daugman and D. M. Kammen, "Image Statistics, Gases and Visual Neural Primitives," First International Conference on Neural Networks, San Diego, CA., June 21-24, 1987, pp. IV-163 to IV-175.